A biphasic curve for modeling, classifying, and predicting egg production in single cycle and molted flocks

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ABSTRACT   Egg production on a flock level can be summarized into several phases determined by biology of individual birds: rapid increase in production reflecting achieving sexual maturity, peak production related to maximum laying potential, followed by gradual decrease in the rate of lay as the birds age. In 1989 Yang et al. proposed a mathematical model (modified compartmental model) to describe this process. In this study a biphasic modified compartmental model was proposed for modeling, classifying, and predicting egg production in single cycle and molted flocks. Goodness-of-fit was high for both single cycle (average $R^2 = 0.99$) and molted flocks (average $R^2 = 0.97$), suggesting that the model could be used for benchmarking molted flocks. The difference in R^2 between the biphasic model and the model used by Yang et al in 1989 can be used to differentiate between single cycle and molted flocks. The biphasic model was shown to predict future records well up to 8 wk in advance, but as with any regression model, caution is recommended when predicting records outside of the observed age range.

Key words: egg production curve, molt, layer chicken

INTRODUCTION

Egg production curves can be used to monitor flock performance (Ramírez-Morales et al., 2017), predict future records (Yang et al., 1989), optimize flock revenue (Long and Wilcox, 2011), quantify persistency of lay (Grossman et al., 2000), and for genetic evaluation (Wolc et al., 2007). Multiple functions have been developed to describe egg production data at the flock level (see review by Anang and Indrijani, 2006), but to our knowledge, none of these are applicable to model production of flocks undergoing molt. Molt, a period of metabolic and physiological changes in birds, leading to cessation of egg production, is a naturally occurring process in birds with seasonal reproduction but can also be induced in domestic poultry by various management techniques (Koelkebeck and Anderson, 2007) to improve egg production and egg quality in older hens (Berry, 2003). Extending already defined models to account for a biphasic production mode can be used to correctly model more complex trait patterns and to categorize them (Islam et al., 2013). Birds undergoing induced-molt lay eggs in 2 separate cycles, which can be described by a biphasic model. The aspect of categorization or classification of single cycle vs. multiple-cycle production curves is particularly important for data collected on a larger scale, where visual inspection is not possible or practical. Field data are critically important to understand performance of commercial hybrids under typical and challenging production environments, but such data sets have limitations derived from partial data or the effect of environmental effects and management practices (climate, disease challenges, nutrition and feeding practices, etc.) on the performance of individual flocks. Correct separation of single cycle from molted flocks allows more accurate data analysis and development of management recommendation. It also allows correct retro feeding of information to breeding programs to guide them toward maximizing commercial hybrid performance.

The objective of this study was to extend model of Yang et al. (1989) to a biphasic form to account for molt and to evaluate its goodness of fit, classification ability, and predictive ability for both molted and single cycle flocks.

MATERIAL AND METHODS

Egg production records (% weekly production) were extracted for 58 single cycle flocks and 44 molted flocks from the Hy-Line International commercial database.

Sampled flocks were required to have production records available until at least 90 wk of age, with cumulative egg counts within expected range. The data represent 9,647,738 layers in flocks with an average size of 94,586 (range 3,740–344,344). The average number of weekly records was 78.7 for single cycle and 79.3 for molted flocks. The data were voluntarily provided by commercial producers across the world; thus, various molting techniques could have been applied. The authors do not have access to the management information of the flocks because data are for monitoring overall variety performance and are not collected within any specific experimental design.

The following models were fitted to the data of each flock separately using the minpack.lm package in R:

Modified Compartmental Model (Yang et al., 1989)

$$y_t = \frac{ae^{-bt}}{1+e^{-c(t-d)}}$$

where:
  a is a scale parameter.
  b is the rate of decrease in laying ability after peak.
  c is the reciprocal indicator of the variation in sexual maturity.
  d is the mean age of sexual maturity of the hens.

Biphasic Model

$$y_t = \frac{ae^{-bt}}{1+e^{-c(t-d)}} + \frac{a_1 e^{-b_1(t-t_0)}}{1+e^{-c_1(t-t_0)}}$$

where: a, b, c, d are parameters equivalent to the above model, modeling egg production in the first cycle, a_1, b_1, c_1 are the same parameters for the second cycle, and t_0 is a parameter describing age at start of the second curve.

Because of its higher complexity, the biphasic model was fitted with a range of starting values for t_0 (65, 75, 85 and 95).

Goodness-of-fit was evaluated as the squared correlation of observed and predicted values (R^2) and mean square error. Predictive ability was tested as forward prediction by removing records from the last 2, 4, or 8 wk of a given flock. The mean square difference between the removed and predicted values was used to evaluate the predicting ability of the models.

RESULTS AND DISCUSSION

Both models showed good fit to single cycle flocks, with an average R^2 of 0.953 for the Yang et al. (1989) model (Yang model) and 0.987 for the biphasic model. This confirms the good fit of the Yang model when applied to single cycle egg production data, as previously reported in the literature (Anang and Indrijani 2006; Wolc et al., 2007; Savegnago et al., 2012; Narinc et al., 2014). In single cycle flocks, biphasic model described egg production in more than just 3 phases, thus resulting in a better fit. For molted flocks, the biphasic model had a clearly better fit, with an average R^2 of 0.973 vs. 0.445 for the Yang model and with respective mean square error of 16.4 vs. 103.8. An example of the fit of these 2 models to real flock data is shown in Figure 1. It must be noted that neither model is bounded to prediction between 0-100% thus values outside the biological limits can be obtained, especially during peak prediction and during molt. Also, it is important to consider that despite the variation in management and environmental conditions represented in the data, the model showed a good fit for the analyzed flocks.

The difference in R^2 between the 2 models allowed 100% correct classification of single cycle vs. molted flocks (Figure 2), which is necessary for correctly benchmarking egg production. When only egg production data of single cycle flocks are used, the second part of biphasic function is expected to become equal to 0 automatically (because all of the parameters referred to post-molting). Therefore, for single cycle flocks, the biphasic model conveniently transforms to Yang model. If the Yang model perfectly fit the data, there would be no variation left for the second part of the biphasic model. However, if the fit is not perfect the biphasic model has an advantage of additional parameters to capture the remaining variation in the data. In such cases, there is improvement in fit at the expense of parameters losing biological
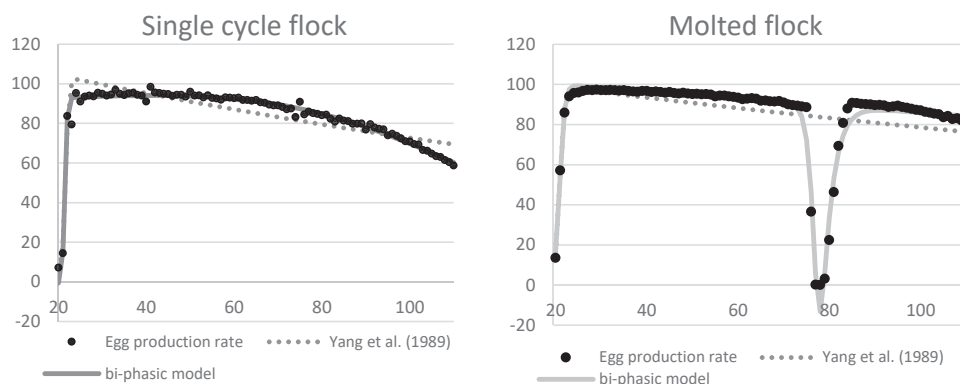

Figure 1. An example of fit of the Yang et al. (1989) and the biphasic model to single cycle and molted flock data.
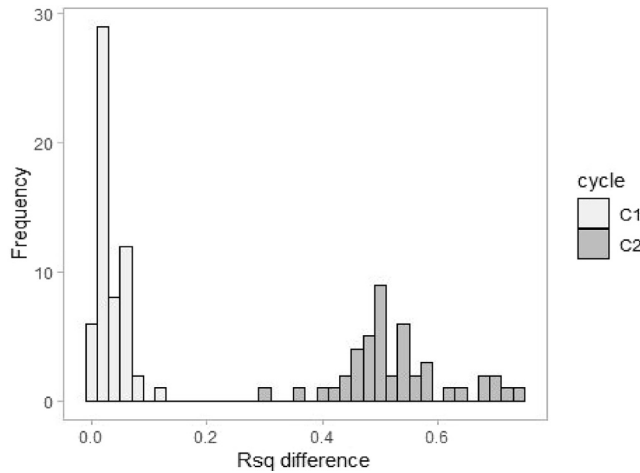
Figure 2. Histogram of the difference in R^2 the Yang et al. (1989) and the biphasic model for single cycle (C1) and molted (C2) flocks.

interpretation. This can be observed on left panel of Figure 1, where the Yang model overpredicted peak production and underpredicted the length of peak production whereas the biphasic model could provide a better fit to the data.

Mean square error of forward prediction for the 2 models is in Table 1. For all cases, except for short-term prediction in molted flocks, the biphasic model had more accurate predictions than the Yang model. Surprisingly, this advantage was larger for single cycle flocks than for molted flocks. Even though dividing egg production into 3 phases, as in the Yang model, is in general a good approximation of the biological process, it does not capture the period of maintained peak production as present in the modern commercial varieties. This extended peak production was accommodated with additional parameters of biphasic model. For molted flocks, the Yang model tended to underpredict production in the second cycle (Figure 1). Because the second cycle of flocks was frequently terminated when a significant drop in production occurred, the Yang model which underpredicted second cycle production, predicted performance in final 2 wk of those flocks well.

As noted in the materials section, the biphasic model can be sensitive to the starting value of the t_0 parameter. Therefore, a range of values was used to correctly model all flocks in the data set. Estimates of the age at the beginning of molt had a wide range in the data analyzed

herein, from 59 to 90 wk of age, with an average of 71 wk. If the starting value was more than 15 wk away from the actual age at molting, unrealistic estimates of model parameters were obtained from the biphasic model. The biphasic model is also potentially more prone to overfitting problematic data (unexplained drops in production), especially in a single cycle setting. Regarding the benefits or advantages of fitting the biphasic model vs. considering 2 separated Yang models (i.e., one per each cycle), one must consider that such an approach would require individual evaluation of each flock and manual determination of age at molt to split the data. While this can be done for a small number of flocks (i.e., in the hundreds rather than in the thousands) as used in this study, it is not practical for large numbers of flocks. One of the reasons for carrying out the research described herein was to use the model for classification of flocks into single cycle and molted. The difference in fit between single and biphasic model classified flocks accurately, and the t_0 parameter estimated the starting age of the second cycle automatically, thus the proposed approach can be applied regardless the data size and the number of flocks included in the analysis.

CONCLUSION

The newly developed biphasic compartmental model is an adequate tool for benchmarking data from molted flocks and for predicting future records. However, caution is advised when predicting outside of the range of observed ages, as is usually recommended for regression models.

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REFERENCES

Anang, A., and H. Indrijani. 2006. Mathematical models to describe egg production in laying hens. J. Ilmu Ternak, 6:91–95.

Berry, W. D. 2003. The physiology of induced molting. Poult. Sci. 82:971–980.

Grossman, M., T. N. Grossman, and W. J. Koops. 2000. A model for persistency of egg production. Poult. Sci. 79:1715–1724.

Islam, Z. U., S. C. Bishop, N. J. Savill, R. R. R. Rowland, J. K. Lunney, B. Trible, and A. B. Doeschl-Wilson. 2013. Quantitative analysis of Porcine Reproductive and Respiratory Syndrome (PRRS) viremia profiles from experimental infection: a statistical modelling approach. PLoS One 8:e83567.

Koelkebeck, K. W., and K. E. Anderson. 2007. Molting layers-Alternative methods and their effectiveness. Poult. Sci. 86: 1260–1264.

Long, A., and S. Wilcox. 2011. Optimizing Egg Revenue for Poultry Farmers, pp. 1–10. Accessed Feb. 2019. https://www. researchgate.net/publication/228452145_Optimizing_Egg_ Revenue_for_Poultry_Farmers.

Narinc, D., F. Uckardes, and E. Aslan. 2014. Egg production curve analyses in poultry science. World Poult. Sci. J. 70:817–828.

Table 1. Mean square error from forward prediction using the Yang et al. (1989) and the biphasic models in single cycle and molted flocks.

Validation	Cycle	Yang	Biphasic
Removed 2 wk	Single	77.5	23.5
Removed 2 wk	Molted	35.3	40.2
Removed 4 wk	Single	75.1	31.2
Removed 4 wk	Molted	40.8	39.4
Removed 8 wk	Single	74.2	62.8
Removed 8 wk	Molted	69.8	40.1

Ramírez-Morales, I., E. Fernández-Blanco, D. Rivero, and A. Pazos. 2017. Automated early detection of drops in commercial egg production using neural networks. Br. Poult. Sci. 58:739–747.

Savegnago, R. P., V. A. R. Cruz, S. B. Ramos, S. L. Caetano, G. S. Schmidt, M. C. Ledur, L. El Faro, and D. P. Munari. 2012. Egg production curve fitting using nonlinear models for selected and nonselected lines of White Leghorn hens. Poult. Sci. 91: 2977–2987.

Wolc, A., M. Lisowski, and T. Szwaczkowski. 2007. Genetic evaluation of laying hens under fixed regression animal models. Arch. Tierz. Dummerstorf 50:279–287.

Yang, N., C. Wu, and I. McMillan. 1989. A new mathematical model of poultry egg production. Poult. Sci. 68:476–481.